World Academy of Science, Engineering and Technology
International Journal of Industrial and Manufacturing Engineering
Vol:11, No:8, 2017

# An Evolutionary Algorithm for Optimal Fuel-Type Configurations in Car Lines

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***Abstract*****—**Although environmental concern is on the rise across Europe, current market data indicate that adoption rates of environmentally friendly vehicles remain extremely low. Against this background, the aim of this paper is to a) assess preferences of European consumers for clean-fuel cars and their characteristics and b) design car lines that optimize the combination of fuel types among models in the line-up. In this direction, the authors introduce a new evolutionary mechanism and implement it to stated-preference data derived from a large-scale choice-based conjoint experiment that measures consumer preferences for various factors affecting clean-fuel vehicle (CFV) adoption. The proposed two-step methodology provides interesting insights into how new and existing fuel-types can be combined in a car line that maximizes customer satisfaction.

***Keywords*****—**Clean-fuel vehicles, product line design, conjoint analysis, choice experiment, differential evolution.

## I. Introduction

TRANSPORT has been one of the sectors most resilient to efforts to reduce $CO_2$ emissions due to its strong dependence on fossil energy sources and its steady growth. Cars continue to be the most popular passenger mode across the EU, representing about 72% of all passenger kilometres and are in-turn responsible for approximately 12% of total EU $CO_2$ emissions [5]. European Nations have seemingly led the way in terms of awareness and concern for the environment, yet it has been argued that there continues to exist an "attitude-action gap" between European consumers' rising environmental consciousness, and willingness to switch from their conventional petrol/diesel, to "greener" fuel vehicles [9]. By approaching CFVs as eco-innovations, the purpose of this study is to a) examine consumer preferences for various factors affecting CFV adoption in the European car market, and b) design consumer driven car lines that optimize the combination of fuel types among models in the line-up. To address these objectives, first, a choice-based conjoint experiment was carried out in two large European countries, namely United Kingdom and Germany. Second, a state-of-the-art, evolutionary mechanism, namely Differential Evolution (DE), is implemented to the preference data in an attempt to design consumer-driven car lines that optimize the combination of fuel-types among car models in the line-up.

## II. Theoretical Background

Literature on CFV choice experiments suggests that there are substantial regional differences in consumer stated preferences for CFV characteristics, and hence, results from different countries are not interchangeable. This study extends research on consumer preferences for CFVs in two ways. First, the sample was drawn in two large European countries, namely Germany and UK, where a large-scale investigation of preferences for CFVs has not been undertaken before. Existing research on CFVs has been conducted in high fossil-fuel pollution areas, such as the USA [12], Canada [6], and China [3]. Second, our choice experiment includes a variety of factors based on the innovation adoption literature. In addition to the typical vehicle-specific predictors (e.g., price), we consider factors with important implications for policy makers.

Literature on optimal product line design has so far utilized a variety of heuristic mechanisms, such as Dynamic Programming [7], Beam Search [8], and Lagrangian Relaxation with Branch and Bound [2]. Nature-inspired approaches have been also introduced to the problem, including Genetic Algorithms [1], and Particle Swarm Optimization [13]. Our study extends research on product line design in two ways. First, we introduce a new mechanism, namely Differential Evolution, for the first time in the area of marketing. Second, this is the first application of a product line optimization mechanism in the area of CFVs.

## III. Methodology

### *A. Conjoint Experiment*

Our study considers eight attributes, ranging across 3 to 4 levels each, resulting in a total of 26 attribute levels (see Table I). Attributes were grouped into five categories; called facets. The facet and attribute selection is based on the innovation adoption literature [10] and a series of in-depth interviews with consumers.

Our choice-based conjoint experiment estimates preferences for vehicle attributes related to four possible fuel types, namely, petrol, diesel, hybrid electric and alternative fuel (such as liquefied petroleum gas, compressed natural gas, or organic biodiesel). Each choice task contained three out of the four fuel types and each participant was randomly assigned to evaluate a total of 12 choice tasks (ordering was also randomized). Our choice-based conjoint experiment was carried out in two EU member states, namely, United Kingdom and Germany and could be accessed online via a closed Web page. A total of 285 respondents participated in our online experiment (153 valid responses were secured from the UK, whilst 132 participants were recruited from Germany). A Hierarchical Bayes model was developed which consists of two levels: At the higher level we assume that

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individual part-worths are described by a multivariate normal distribution, $\beta_i \sim \mathrm{Normal}(\alpha, D)$, where $\beta_i$ is a vector of part-worths for the *i*th individual, $\alpha$ is a vector of means of the distribution of individuals' part-worths, and $D$ is a matrix of variances and covariances of the distribution of part-worths across individuals. At the lower, individual level, it is assumed that given an individual's part-worths, his/her probability of choosing a particular alternative is described by a multinomial logit model. The $\beta, \alpha, D$ parameters were estimated using the Monte Carlo Markov Chain iterative process. A detailed explanation of this algorithm is beyond the purpose of this paper.

TABLE I
THE 8 VEHICLE ATTRIBUTES AND 26 ASSOCIATED LEVELS, CATEGORIZED UNDER 4 FACETS

| Facet | Attribute | Level 1 | Level 2 | Level 3 | Level 4 |
|---|---|---|---|---|---|
| Relative advantage | Fuel type | *Petrol* | *Diesel* | *Hybrid Electric* | *Alternative Fuel (such as LPG, CNG, or organic biodiesel)* |
| | Vehicle's purchase price | *£14,000* | *£17,000* | *£21,000* | |
| | Fuel cost (per 100km) | *£5* | *£10* | *£20* | |
| | $CO_2$ emissions (per km) | *95g* | *130g* | *170g* | *250g* |
| Compatibility | Vehicle's fuel availability | *At all filling stations* | *At 3 out of 4 filling stations* | *At 1 out of 4 filling stations* | |
| Ease of use | Vehicle's maintenance effort | *Easy to maintain* | *Standard to maintain* | *Complex to maintain* | |
| Trialability | Test drive opportunity | *Week-long trial* | *1 hour test-drive* | *Test-drive not possible* | |
| Financial risk | Tax breaks on fuel | *Guaranteed until 2020* | *Guaranteed until 2015* | *No tax-breaks* | |

*B. Differential Evolution: Implementation to the Car Line Design Problem*

DE was introduced by [11] and belongs to the class of Evolutionary Algorithms (EAs). Evolution is the process of adaptation with the aim of improving the survival capabilities through mechanisms such as natural selection, survival of the fittest, reproduction, mutation, competition and symbiosis [4]. Companies and products strive to adapt and survive in fast changing and highly competitive global markets, in the same way that species and individual organisms do in the natural environment. In both cases the goal is the determination of the strongest individuals (i.e., products) that possess the most desirable genetic material (i.e., characteristics), and have the best probabilities to survive, in accordance with Charles Darwin's theories on "natural selection" and "survival of the fittest". EAs are applied to complex real world problems, representing candidate problem solutions with individuals that recombine their genetic material. Like almost all EAs, DE "attacks" the problem space from multiple locations by generating a population of individuals. Each individual represents a potential solution to the problem, whose performance is evaluated against the problem's objective function. An initial population is generated randomly and an iterative procedure follows, where a set of operators is applied. A distinct feature of DE is that the mutation is applied first (unlike most of the other EAs that first apply crossover) to produce a *trial* vector, which is used in the crossover process.

*Mutation:* In DE, the mutation process comprises three different vectors. Specifically, for every individual $i$ in the population, a *target* vector $i_1$, as well as two *differential* vectors $i_2$ and $i_3$ are selected from the population such that $i \neq i_1 \neq i_2 \neq i_3$. The *trial* vector $t_i$ for individual $i$ is generated by adding a scaled perturbation of vectors $i_2$ and $i_3$ to the target vector $i_1$:

$$t_i = x_{i1} + \beta * (x_{i2} - x_{i3}) \tag{1}$$

where the scale factor $\beta$ is a positive real number in [0, 2] that controls the amplification of the differential variation, which in turn controls the rate at which the population evolves. Small values of $\beta$ favour local search, while large values favour global search. A value of 0.5 is usually employed to achieve balance between the two.

*Crossover:* Once the trial vector is created for individual $i$, the crossover operator is applied as a discrete recombination of the material of the two vectors:

$$x'_{ij} = \begin{cases} t_{ij}, & \text{if } rand_j \leq Cr \\ x_{ij}, & \text{otherwise} \end{cases} \tag{2}$$

where $x_{ij}$ corresponds to the $j^{th}$ element of vector $x_i$. $Cr \in [0,1]$ is the crossover probability, a user defined parameter, and $rand_j$ is the output of a uniform random number generator in (0, 1). This refers to the *uniform crossover* used in the original version of the algorithm. The higher the value of $Cr$, the larger the fraction of values that are taken from the trial vector.

*Selection:* The individual that will survive to the next generation's population is deterministically selected. That is, the performance of the offspring ($x'_i$) on the problem's objective function is compared to that of the parent ($x_i$). The one that performs better is added to the next generation. The individuals of the next generation also undergo mutation, crossover and selection, and the algorithm iterates until a terminating condition is met.

To design a consumer-driven line of cars that optimizes the combination of fuel types offered, we apply the DE algorithm to the empirical stated-preference data set. We employ a binary representation scheme, where each element of the solution vector represents an attribute level. For a single-car line the number of elements (i.e., vector's length) is 26, which is the total number of attribute levels included in the conjoint experiment. Under such a representation scheme a constraint must be applied which ensures that within each attribute only a single element takes the value of 1 (a single level is chosen). For example, a Diesel car, priced at £21,000, with £5 fuel cost per 100 km, 95g $CO_2$ emissions per km, fuel availability at all filling stations, standard maintenance effort, 1 hour test drive opportunity, and no tax-breaks, would be represented as [0100 001 100 1000 100 010 010 001]. For multiple-car lines the vector's length is $26*l$ where $l$ is the number of different car models in the line. That is, elements 1-26 correspond to the attributes levels of the first car model, elements 27-52 correspond to the attributes levels of the second car model, and so on. DE operates in a continuous space, and hence, for a two-decimal points representation, a potential vector for a single-car line could be: y = [1.54 0.24 -8.24 4.25 1.66 0.87 -0.54 6.78 6.25 -1.53 3.02 7.01 8.30 0.88 -4.28 1.47 -2.93 2.60 4.58 -3.54 5.67 0.11 -3.27 0.78 -0.88 4.38]. To convert such a vector to the required binary representation, we employ the modified Smallest Position Value (SPV) rule: within each attribute, the element with the smallest value takes a value of 1, and the rest take a value of 0. In that case, vector $y$ is converted to [0010 001 001 0001 100 001 001 010]. With regard to the DE control parameters, [11] indicated that a reasonable choice for $NP$ is between $5D$ and $10D$ (where $D$ is the dimensionality of the problem), and $\beta = 0.5$ is usually a good choice. We tested different values for $NP$, $Cr$, and maximum number of iterations. The algorithm worked well with a population size at the lower end of the range [$5D$, $10D$], that is $NP$=130 for a single-car line problem, $NP$=260 for a two-car line problem, and so on. The best performance was achieved for $Cr$=0.8, and the algorithm converged to a solution at 1000-1200 iterations, so we set the maximum number of iterations to 1500. To define the problem's objective function we employ the "buyers' welfare criterion", where the objective is the maximization of the total utility of all buyers that comprise the market. We employ the first choice (maximum utility) rule, according to which each buyer will deterministically choose the car that gives him/her maximum utility. Hence, for every solution that the algorithm produces, we calculate the utility value $u_{ij}$ that each car $j$ in the line offers to a customer $i$ as the sum of the part-worths of the chosen attribute levels: $u_{ij} = \sum_{k=1}^{8} w_{ijk}$ , where $w_{ijk}$ is the part-worth that customer $i$ assigns to the level that is chosen for the $k^{th}$ attribute of the $j^{th}$ car in the line. From all the cars in the line each customer is assigned the one that maximizes his/her utility. Finally, the fitness of a candidate solution is the sum of the utilities of all customers.

## IV. Results

### A. Facet and Attribute Importances

Facet importances are presented in Fig. 1. Results suggest that the most important facet in both markets is the vehicle's "Relative advantage", followed by "Compatibility" and "Ease of use". Fig. 2 illustrates the importances of the eight attributes. "Fuel cost" is the most important determinant of vehicle choice in both markets, followed by "fuel type" and "purchase price". Also, it is evident that British consumers place more emphasis on the vehicle's fuel cost compared to German consumers, while German consumers seem to place more emphasis on the vehicle's purchase price compared to British consumers. Also, fuel availability seems to be much more important among British consumers than it is among German consumers.

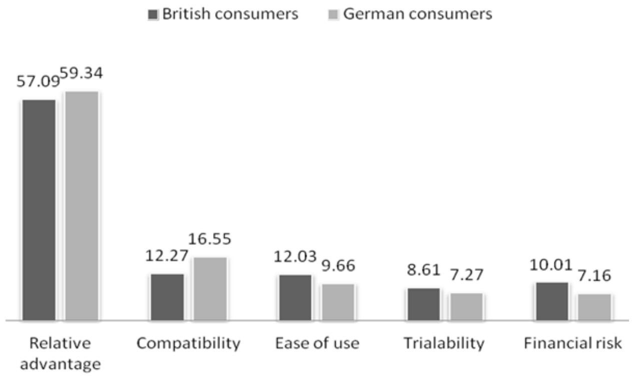


Fig. 1 Estimated facet importances

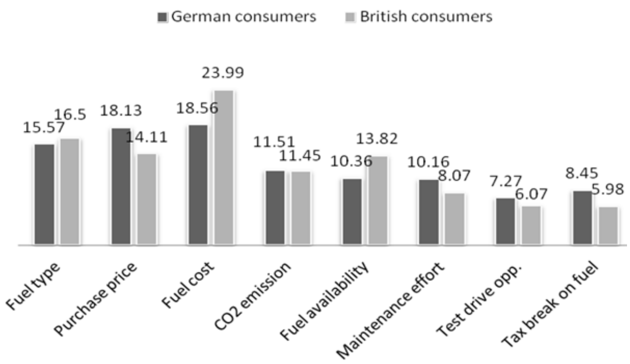


Fig. 2 Estimated attribute importances

### B. Derived Optimal Car Lines

The results show that for $n$=5 cars in the line, the gain in the total utility of the line is too small. Thus, the length of the car line should be chosen among 1, 2, 3, and 4. Tables II and III report the configurations of the car models in the line for the best solutions reached by the algorithm, for the whole consumer group, and the two countries separately. The choice share of each model (i.e., percentage of consumer that are assigned to), and the total line utility (i.e., fitness of the solution), are also presented. Table II presents the derived optimal car lines for the whole consumer sample. It is evident that the car configuration of the single-car line solution is also included in the two-car line solution; the car configurations of the two-car line solution are also included in the three-car line solution, and so on. This pattern illustrates how new and existing fuel-types must be combined in a car line-up which successively extends to include new car models. More specifically, the single-car line solution represents a diesel car, priced at £14,000, which costs £5 to run per 100km and emits 95gr of CO2 per km. The two-car line solution includes the diesel car of the single car line and is also extended to include a hybrid electric car as a second option. Finally, an alternative fuel vehicle is added in the three-car line solution, and a petrol car (highly priced at £21,000), is added as a last option in the four-car line solution. All four available fuel-types are included in the four-car line solution. This is logical as our sample is diverse and consists of both British and German consumers.

TABLE II
CONFIGURATION OF CAR MODELS FOR LINES OF DIFFERENT LENGTHS

| | | | Fuel type | Vehicle's purchase price | Fuel cost (per 100km) | $CO_2$ emissions (per km) | Vehicle's fuel availability | Vehicle's maintenance effort | Test drive opportunity | Tax breaks on fuel | Choice Share | Total Line utility |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| All | Single-car line | 1st | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 100% | 33690 |
| | Two-car line | 1st | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Hour | 2020 | 50% | 37778 |
| | | 2nd | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 50% | |
| | Three-car line | 1st | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Hour | 2020 | 42.8% | 39287 |
| | | 2nd | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 42.5% | |
| | | 3rd | Alternative Fuel | £14,000 | 5 | 95g | 3/4 | Easy | Week | 2020 | 14.7% | |
| | Four-car line | 1st | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Hour | 2020 | 41.1% | 39887 |
| | | 2nd | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 38.2% | |
| | | 3rd | Alternative Fuel | £14,000 | 5 | 95g | 3/4 | Easy | Week | 2020 | 13.3% | |
| | | 4th | Petrol | £21,000 | 10 | 95g | All | Easy | Week | 2020 | 7.4% | |

TABLE III
CONFIGURATION OF CAR MODELS FOR LINES OF DIFFERENT LENGTHS

| | | | Fuel type | Vehicle's purchase price | Fuel cost (per 100km) | $CO_2$ emissions (per km) | Vehicle's fuel availability | Vehicle's maintenance effort | Test drive opportunity | Tax breaks on fuel | Choice Share | Total Line utility |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| UK | Single-car line | 1st | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 100% | 16715 |
| | Two-car line | 1st | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Hour | 2020 | 54.2% | 19078 |
| | | 2nd | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 45.8% | |
| | Three-car line | 1st | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Hour | 2020 | 48.4% | 19682 |
| | | 2nd | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 41.8% | |
| | | 3rd | Petrol | £21,000 | 10 | 95g | 3/4 | Easy | Hour | 2020 | 9.8% | |
| | Four-car line | 1st | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 43.1% | 19991 |
| | | 2nd | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Hour | 2015 | 24.2% | |
| | | 3rd | Hybrid Electric | £14,000 | 5 | 95g | 3/4 | Easy | Hour | 2020 | 23.5% | |
| | | 4th | Petrol | £21,000 | 10 | 95g | 3/4 | Easy | Hour | 2020 | 9.2% | |
| Germany | Single-car line | 1st | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 100% | 17024 |
| | Two-car line | 1st | Diesel | £14,000 | 5 | 95g | All | Easy | Hour | 2020 | 62.9% | 18980 |
| | | 2nd | Alternative Fuel | £14,000 | 5 | 95g | 3/4 | Easy | Week | 2020 | 37.1% | |
| | Three-car line | 1st | Diesel | £14,000 | 5 | 95g | All | Easy | Week | 2020 | 40.9% | 20163 |
| | | 2nd | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Hour | 2020 | 32.6% | |
| | | 3rd | Alternative Fuel | £14,000 | 5 | 95g | 3/4 | Easy | Week | 2020 | 26.5% | |
| | Four-car line | 1st | Hybrid Electric | £14,000 | 5 | 95g | All | Easy | Hour | 2020 | 35.6% | 20500 |
| | | 2nd | Diesel | £14,000 | 5 | 130g | All | Easy | Week | 2015 | 26.5% | |
| | | 3rd | Alternative Fuel | £14,000 | 5 | 95g | 3/4 | Easy | Week | 2020 | 26.5% | |
| | | 4th | Diesel | £14,000 | 10 | 95g | All | Standard | Hour | 2020 | 11.4% | |

We now turn to derive localized car line solutions. Table III reveals that the two markets differ significantly with each other.

First, the optimal car lines of the German market differ across the derived solutions. For example, the car configuration of the single-car line solution is not included in the two-car line solution, suggesting discrepancies between a uniform and a differentiated approach to the market. More specifically, the single-car line solution represents a hybrid electric car, while the two-car line solution represents a diesel and an alternative fuel vehicle. On the other hand, the UK market requires a more uniform approach, as the car configuration of the single-car line (i.e., diesel car) is also included in the two-car line solution. Second, the car lines of the UK market include at least one diesel car in every car line solution, but this is not the case in the German market, which includes a hybrid car in the single car line solution. Third, the UK market's three- and four-car line solutions include a petrol-fuelled car, but the latter fuel type does not appear in any of the German market's solutions. Fourth, the German market's two-, three- and four-car line solutions include an alternative fuel vehicle, but the latter fuel type does not appear in any of the UK market's derived solutions. Fifth, UK consumers seem more willing to accept a higher price for a car, as there are two car configurations priced at £21,000 (both of them represent petrol cars), which do not appear in any of the German market's optimal solutions. Evidently, German consumers are more price-conscious and prone to buy CFVs compared to their UK counterparts, who are willing to pay a higher price for a petrol car. Also, the German market is more heterogeneous as few of the derived car-line solutions share common car configurations. The UK market is less heterogeneous as the variant of the single-car line solution is included in the diversified car-line solutions. Obviously, car manufacturers must use different diversification strategies in the two regions, which involve much more complex decisions than merely adding new variants in existing car lines.

## V. Conclusion

The EU's emission limits are set according to the mass of the vehicle, using a limit value curve. Only the fleet average is regulated, therefore manufacturers are able to make vehicles with emissions above the limit value curve provided these are balanced by vehicles below the curve [5]. Our proposed two-step methodology provides interesting insights into how conventional and clean-fuel types must be combined in a diversified car line that maximizes customer satisfaction. This mechanism can be useful for car manufacturers who want to design balanced car line-ups by combining vehicles with emissions above and below the limit value carve imposed by the EU. Although manufacturers have still a long way to go in their effort to meet European Commission's climate and energy regulations, we believe that studies like this one are particularly useful. We hope that our ideas will stimulate more work in this important and quite neglected area of research.

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